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Maize yield under a changing climate in the Brazilian Northeast: Impacts and adaptation

Minella Alves Martins*, Javier Tomasella, Cássia Gabriele Dias

CEMADEN, Centro Nacional de Monitoramento e Alertas de Desastres Naturais, Cachoeira Paulista, SP, Brazil

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ABSTRACT

This paper assessed the potential impacts of climate change on maize productivity in the Brazilian Northeast. To achieve this objective, bias-corrected regional downscaled scenarios from three global models for the representative emission pathways, RCP4.5 and RCP8.5, for the periods 1980–2005, 2007–2040, 2041–2070, and 2071–2099 were used as input data for a crop productivity model. Because increased temperatures are likely to shorten the crop cycle length, thus reducing productivity, we investigated the lengthening of the growing cycle as an adaptation strategy. To cope with the reduction of rainfall projected by future climate scenarios, we analyzed the potential impact of irrigation on productivity. The results showed that climate change effects would be mostly negative for maize rainfed agriculture, particularly for the worst-case scenario (RCP8.5, 2071–2099), in which losses were expected to reach more than 60%. However, productivity losses were limited to a maximum of 30% for all RCP4.5 scenarios and before 2070 for the RCP8.5 scenario. The use of maize cultivars with a longer crop cycle for rainfed agriculture was likely to increase the average productivity in all scenarios, although it came at the expense of increasing the risk of crop failure. Regarding the use of irrigation, there was an improvement in productivity for both the short- and long-cycle cultivars, although longer crop cycle cultivars had a decisive advantage, with a drop in yield of less than 20% for all RCP4.5 scenarios and for the RCP8.5 scenario until 2070 compared to the present climate. We estimated the total production and the increase in water demand based on the existing and projected irrigated areas in the region and concluded that it is possible to avoid significant losses in total maize production in the region for all scenarios, with the exception of the 2071–2099 RCP8.5 scenario. However, sustaining such levels of production requires a significant increase in water consumption (up to 140%).

1. Introduction

According to the fifth IPCC report (IPCC, 2014), the projected increases in atmospheric CO_2 concentration and temperature, changes in rainfall patterns and water availability, and the intensification of climate extremes are likely to affect the economy, environment and societal sectors. Regarding crop yield, those changes might result in a wide variety of impacts (Asseng et al., 2013; Porter et al., 2014; Trnka et al., 2014), with productivity increasing in many regions and declining in others (Challinor et al., 2014; IPCC, 2014; Wheeler and von Braun, 2013). It is expected that climate changes will affect the sustainability of agricultural systems in many regions, and the populations who depend on local food production will be most vulnerable (Wheeler and von Braun, 2013; Müller et al.,2011; Asante and Mensah, 2015). In this context, food security will face significant challenges, particularly in semiarid environments, and cropping technologies will be essential to sustaining production levels for an increasing population in the stressed environment due to global warming.

In the context of climate change, the northeast region of Brazil is considered to be one of the most vulnerable regions in the country (Marengo et al., 2016; Simões et al., 2010) due to its high population exposure, high poverty rates, and low adaptive capacity. The inner region of northeast Brazil is largely semiarid, characterized by relatively low and high variability in space and time of the rainfall, combined with high evaporation rates. The region is affected by periodic droughts with severe socioeconomic impacts on the local population and substantial impacts on the public expenditure on mitigation actions. Recent studies (Brito et al., 2017; Marengo et al., 2017) suggest that there has been an intensification of both the duration and frequency of severe droughts. Agricultural production depends on

* Corresponding author at: CEMADEN, Centro Nacional de Monitoramento e Alertas de Desastres Naturais, Cachoeira Paulista, SP, Brazil.
E-mail addresses: minella.martins@cemaden.gov.br, minella.martins@gmail.com (M.A. Martins), javier.tomasella@cemaden.gov.br (J. Tomasella), cassia_dias08@hotmail.com (C.G. Dias).

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smallholder farmers that cultivate under rainfed conditions with low technological resources. Farming methods in the region include fire-fallow and shifting cultivation, which has resulted in increased deforestation rates of the shrublands (locally known as *Caatinga*). In addition, livestock has become the main economic activity since the 19th century. Inadequate management practices and overexploitations of natural resources has resulted in increased desertification of the area (Vieira et al., 2015; Tomasella et al., 2018).

The most widely produced grain in the Brazilian Northeast is maize (*Zea mays* L.), which not only is an important staple food of the local population but also is used to feed animals. Although maize is one of the most versatile cereal crops, previous studies showed that its growth and productivity are likely be affected by increased atmospheric CO_2 and higher temperatures. While higher temperature negatively affects the growth, yield and quality of maize, the effects of elevated CO_2 on the yield of maize are contradictory: from little positive effect (Leakey et al., 2004), to no effect (Kim et al., 2007), to an increase of yield by 50% (Vanaja et al., 2015). A recent study by Abebe et al. (2016) in northwest India revealed that maize responded positively to higher atmospheric CO_2 concentrations and negatively to higher temperature. The study also indicated that elevated CO_2 was able to reduce the negative effect of elevated temperature on maize yield. However, the reduction of average precipitation, the increased frequency of extreme events such as drought, and the increase of temperature in northeast Brazil (Marengo et al., 2017) might have counterbalancing effects. Therefore, understanding the combined effects of increased CO_2 and the unfavorable climate conditions for agricultural is crucial for ensuring preparedness and for developing adaptation strategies.

Due to the uncertainties of climate change projections, impact assessments should use multimodel climate projections rather than single model approaches to generate a range of plausible scenarios (Taylor et al., 2009). For this reason, the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012) provides estimates of future climate change around the world based on data from more than 40 global climate models (GCMs), with a grid size ranging from 100 to 200 km. Since this spatial resolution is inadequate for studies that focus on small-scale climate change impacts, there is a reliance on the use of regional atmospheric models that allow for horizontal resolutions at the level of tens of kilometers that enable explicit simulations of mesoscale processes with a better representation of local climatic characteristics (Tavares et al., 2018). In the case of Brazil, Chou et al. (2014a, b) showed that dynamic downscaling techniques provide more accurate climate simulations, particularly in terms of the intensity and frequency of extreme precipitation events. Consequently, in this study, downscaled climate scenarios for northeast Brazil of the regional climate model Eta (Mesinger et al., 2012), nested in three CMIP5 GCMs models, were used as input for the AquaCrop model (Raes et al., 2009; Stetuto et al., 2009) to assess the potential impacts of climate change on maize in terms of yield, biomass, water use efficiency, planting dates, and crop cycle length. Input datasets included the representative concentration pathways, RCP4.5 and RCP8.5, as the climate change drivers.

Previous studies (for instance, Xiao et al., 2015) have shown that under warmer climate conditions, maize yield might also be reduced due to early flowering and maturity and consequently shorten reproductive growth stage. This is particularly relevant in the semiarid northeast Brazil, where the need to cope with water shortage and the large intraseasonal rainfall variability have promoted the development of short crop cycle maize varieties.

Therefore, we investigated whether potential adaptation measurements, specifically the lengthening of the crop cycle (Mueller et al., 2015), could minimize adverse climate change effects.

Since field studies concluded that irrigated maize under elevated CO_2 levels have a positive effect on water use efficiency, resulting in higher yields (Meng et al., 2014; Araya et al., 2017), we also estimated the attainable productivity of irrigated maize for both short and extended crop cycle varieties and the impacts of the expansion of irrigated areas on water demand for the baseline and future scenarios.

2. Material and methods

2.1. Description of study region

The study region is located in northeast Brazil and covers an area of approximately 1.5 million km^2, which is 20% of the total Brazilian territory (Fig. 1). Due to its extension, rainfall is modulated by multiple atmospheric systems, such as the intertropical convergence zone in the northern part of the region, the upper cyclonic vortex, the easterly wave disturbances, squall lines in the central part, frontal systems, and the South Atlantic convergence zone in the southern part of the region (see details in Oliveira et al., 2017). The annual rainfall is less than 500 mm in the semiarid inner areas and more than 1500 mm in the coastland and in the northwest part of the region, which has resulted in various Köppen climate types (Fig. 1). The climate of the whole area alternates between a wet season, for which timing and characteristics vary throughout the region but generally last between 2–5 months, and a dry season for the remainder of the year. Rainfall is characterized by high spatial variability combined with large intraseasonal to interannual variations (Cunha et al., 2015). Based on the frequency of rainy days over a four-month period, Cunha et al. (2015) divided the area into five sub regions, which are entirely consistent with the different rainfall regimes (Fig. 1).

With more than 50 million inhabitants (~26% living in rural areas) (IBGE, 2010), a large part of the population of the study area depends on agriculture in the classic model of subsistence agriculture (IPEA, 2018). In this context, agricultural production in NEB is a meaningful source of income, especially for family farming[1], which is responsible for 82.6% of the jobs in rural areas and 50% of the value of marketed production. In addition, agriculture and livestock sectors contribute to almost 30% of NEB's gross domestic product - GDP (IPEA, 2012). Maize production, mainly by rainfed production systems, and modest livestock rearing are the mainstays of household livelihoods in the area.

The government, private companies and social organizations have invested in water infrastructure to promote mitigation actions in NEB and to improve traditional agricultural management practices. Successful initiatives in the São Francisco River Valley involve irrigated fruit cultivation (IPEA, 2018). Obermaier et al. (2014) have shown examples of pilot irrigation projects that used small dams in the region to store water. Although these reservoirs are often sufficient for irrigated agriculture (Carvalho and Egler, 2003), inefficient irrigation practices are still in use at small properties. Positive actions have contributed to mitigate the drought effects on agricultural production, although more efficient water management is needed (IPEA, 2018).

2.2. Meteorological data

We integrated rain gauge data from different sources, including the Brazilian Water Agency (ANA) and the Brazilian National Weather Service (INMET), resulting in a database with daily data from approximately 4000 rain gauges, as described in Souza et al. (2001) (see Figure A1 in Supplementary material). In addition, observations from more than 300 meteorological stations from INMET were used to calculate the Penman-Monteith reference evapotranspiration according to Allen et al. (1998).

The station data was then interpolated to a spatial resolution of 5 km using the inverse of the squared distance and for the period 1980–2005 for the following variables: rainfall, reference

[1] The definition by the Brazilian Family Farming Act (Law n. 11.326) is that it is an agricultural producer that is directly responsible for farm management, uses mainly family labor and earns a substantial part of the total family's income from agricultural activities (Brazil, 2006).

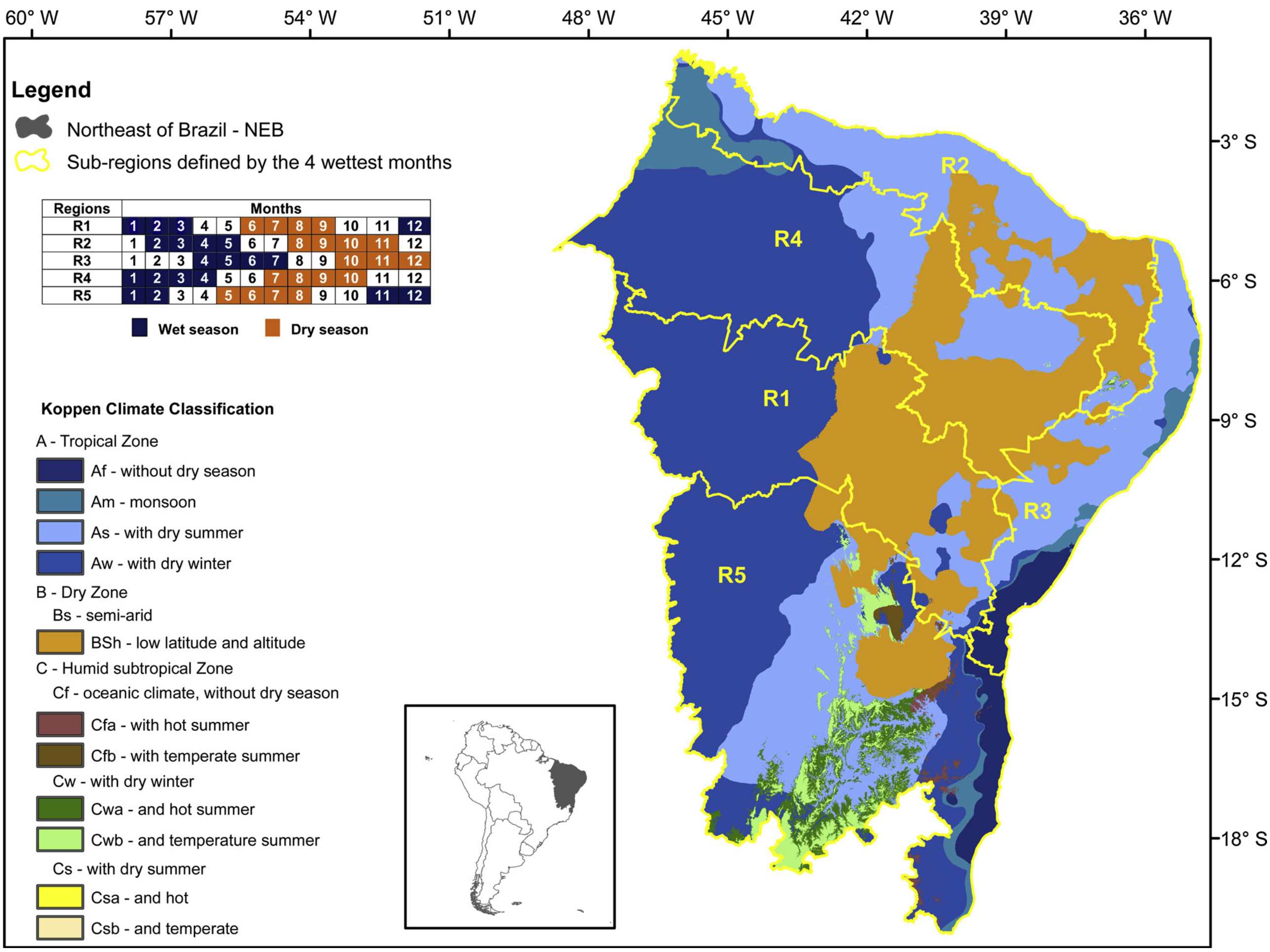

Fig. 1. Map of the study area showing the subregions (yellow polygons) defined by the wettest months (Cunha et al., 2015) and Köppen climate classification Alvares et al. (2013) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

evapotranspiration, and maximum and minimum temperature. The same spatial resolution has been adopted in previous studies for an adequate representation of the spatial variability of rainfall (Souza et al., 2001). Considering the size of the region and the grid resolution, the number of pixels use to represent the study area was 57,504 valid points.

These datasets were used to validate the climate projections for the present climate (baseline scenario) over the period 1980–2005.

2.3. Crop and irrigation area data

Crop productivity data used in this work were those compiled by Martins et al. (2018). Those data sets include 45 experiments from 20 locations.

Those experiments include a mix of maize cultivars (3–4 months from planting to harvest) used in the semiarid area, which were tolerant of water deficit and the high temporal variability of the rainfall during the growing season.

We also explored the use of irrigation on maize productivity and the overall regional production.

To achieve this goal, the total planted area of maize for each municipality of the study region was extracted from the Municipal Agricultural Production - PAM (IBGE, 2016). Because not all of the available agricultural land is appropriate for irrigation, we used estimations based on the data from the Brazilian Atlas of Irrigation (ANA, 2017), which quantified the irrigated area in 2015 and the potential expansion of irrigated areas in 2030 for each municipality of the study region (Figure A2 in the Supplementary material). The expansion takes into account the water availability, crop requirements, available areas for agriculture considering environmental restrictions, infrastructure and logistics, land tenure, and agricultural aptitude based on soil and topography. The current irrigated area in NEB is approximately 1.3 million ha, and the potential irrigated agricultural expansion is approximately 11% (ANA, 2017).

2.4. Soil database

The soil database used in this study includes approximately 1200 Brazilian pits from conventional soil surveys conducted by the Brazilian Agricultural Research Corporation (EMBRAPA) and are reported in Souza et al. (2001). Data were obtained on the soil type, horizon description and depths, the physical characteristics (texture and stoniness) and chemical data for each horizon (see Figure A1 in Supplementary material). We used the pedotransfer functions proposed by Tomasella et al. (2003) to estimate (i) water contents at field capacity, saturation and wilting point, (ii) the saturated hydraulic conductivity and (iii) the amount of gravel for 10 different depths (0.10, 0.20, 0.30, …0.60, 0.80, 1.00, …, 1.60 m), at each soil pit location.

To take into account the spatial variability of soil types, we used the soil map of Vieira et al. (2015) to group the soil pits included in each map unit. The soil hydraulic properties of each horizon were interpolated to a 5 km grid for each soil map unit separately and then were merged for the whole area. Although this interpolating technique has limitations for representing the whole range of spatial variability of soils, it should be considered that the resulting soil hydraulic map represents the averaged properties over a 5 km squared grid. In addition,

the density of the soil sampling of the available soil surveys is relatively scarce in relation to the size of the study area.

2.5. Climate projections

We used six sets of 20 km spatial resolution downscaled simulations of the Eta Regional Climate Model (RCM) forced by three global CMIP5 climate models for two representative concentration pathways (RCP) for carbon emissions: the CanESM2, HadGEM2-ES, and MIROC5 (Arora et al., 2011; Collins et al., 2011; Watanabe et al., 2010). Those global models were previously evaluated by Chou et al. (2014a,b, 2018) in a study on South America and showed better performance in representing the current climate; for this reason, the models were used to support the Brazilian Third National Communication to the United Nations Framework Convention on Climate Change - UNFCCC (Brazil, 2016b).

According to the 5th IPCC report (2014), the RCP4.5 and the RCP8.5 scenarios represent optimistic and pessimistic emission scenarios, respectively. In the present study, time-slices for the periods 1980–2005, 2007–2040, 2041–2070, and 2071–2099 were used to represent the baseline and future climate, respectively.

Daily maximum and minimum temperatures, dew point temperature, atmospheric pressure, wind speed at 10 m height and solar radiation of the downscaled scenarios were used to estimate the reference evapotranspiration using the Penman-Monteith method according to Allen et al. (1998). To match the interpolated soil hydraulic and meteorological data maps, the Eta regional scenarios were further refined from a 20 km grid to a 5 km grid using bilinear transformation.

Climate projections were bias-corrected to eliminate systematic errors using the method proposed by Bárdossy and Pegram (2011), which has been successfully used in the region by Martins et al. (2018). This method assumes that the bias is determined by displacement (for the same level of experimental frequency) of the cumulative distribution functions derived from observations and from model simulations. Therefore, cumulative distribution functions were determined for each grid cell and for each month based on observations (described in item 2.2) and climate model simulations for the baseline scenario (1980–2005), which were afterwards used to eliminate the systematic errors of all regional scenarios.

2.6. Crop productivity model

In a previous study in the same area, Martins et al. (2018) showed that the AquaCrop model (Raes et al., 2009; Stetuto et al., 2009) had good performance in predicting the attainable maize yield. The AquaCrop model takes into account the impacts of water stress caused not only by stomatal closure but also by reductions in leaf expansion and premature canopy senescence. In addition, AquaCrop accounts for the effects of temperature on crop growth and the impacts of elevated atmospheric carbon dioxide concentrations on crop productivity, which makes it suitable for this study. Given the large spatial domain and the number of evaluations required, we used the open-source version of the FAO AquaCrop model (Foster et al., 2017).

The AquaCrop model is capable of estimating crop productivity based on either fixed length of the crop cycle (calendar days - CAD) or on growing degree days (GDD). Simulation runs produced the daily outputs of several variables, such as yield (t ha^{-1}), biomass (t ha^{-1}), transpiration (mm), water productivity (kg m^{-3}), planting date, crop cycle (day) and irrigation (mm).

In addition to the climate (described in item 2.2) and soil data (indicated in item 2.4), AquaCrop requires information about the crop parameters that needs to be calibrated for use in field data, as well as the initial soil moisture conditions of the crop cycle. In addition, the model requires a time-series of CO_2 concentrations to run projections.

2.7. Maize scenario simulations

We used two sets of AquaCrop-calibrated crop parameters for maize yield simulations.

- Those parameters calibrated by Martins et al. (2018) using a fixed calendar of 120 days, hereafter referred to as CAD, where this length cycle represents most of the cultivars in that area and provides enough accurate results (see details in Martins et al., 2018).
- Crop parameters calibrated for growing degree days using the crop data set of item 2.3, hereafter referred to as GDD.

These different sets of crop parameters were used to examine adaptation strategies as described in Section 2.8. In addition, simulations used a time-series of CO_2 atmospheric concentrations extracted from the RCP4.5 and RCP8.5 IPCC scenarios.

Although the original version of AquaCrop (Raes et al., 2009; Stetuto et al., 2009) considered the effects of soil fertility and salinity stresses, these features were not included in the current version of AquaCrop-OS (Foster et al., 2017). Therefore, maize yield simulations conducted in this study include all physiological stresses related to elevated temperature, CO_2 concentration and water deficit but did not consider conditions of limited soil fertility or elevated soil salinity. This simplification is further justified by the fact that the calibration parameters derived by Martins et al. (2018) are based on controlled field experiments where both fertility and salinity levels are within the recommended ranges.

Bias-corrected maximum and minimum temperatures and the reference evapotranspiration and rainfall for both the baseline period and projections for the near future, middle and end century of the three CMIP5 global models, dynamically downscaled over the study area, were used as the input for the AquaCrop-OS model.

Using the calibrated crop parameters and soil hydraulic characteristics at 5 km spatial resolutions, we estimated maize crop productivity by observing the wettest four-month period of each of the five subregions considered in Fig. 1. Planting dates for each simulation were not fixed but were determined by 5 consecutive days with at least 30 mm cumulative rainfall. This approximation mimics the traditional management practices of smallholder farmers of the region that "wait for the rainfall to plant" rather than following a fixed calendar, and it allows for variations in the onset of the wet season under future climatic conditions. In addition, we verified that the adopted amount of rainfall provides enough initial moisture in the soil profile to ensure germination. Due to the high interannual rainfall variability, we assumed that there was complete crop failure whenever the amount of rainfall for triggering planting was not achieved in the first two months of the wet period of each subregion.

To evaluate the ability of downscaled scenarios to predict crop productivity, we compared the crop productivity by using interpolated observations as inputs against the productivity derived by using the bias-corrected climate scenarios. The quality of the agreement was assessed in terms of the pixel-to-pixel correlation index and the root square error of the averaged productivity over the baseline period 1980–2005 for both estimations for the whole study area.

Finally, crop productivity projections for the RCP4.5 and RCP8.5 scenarios for the periods 2007–2040, 2041–2070, and 2071–2099 were compared to the baseline scenario 1980–2005. Results were grouped according to the five subregions considered in Fig. 1.

2.8. Cropping system adaptation alternatives

Although the increase in CO_2 concentration typically leads to higher plant water-use, efficiencies that positively influence maize productivity (Rolla et al., 2018), the shortening of the growing season is associated with higher air temperatures to reduce the grain-filling period (Huang et al., 2017; Lizaso et al., 2018), which causes a

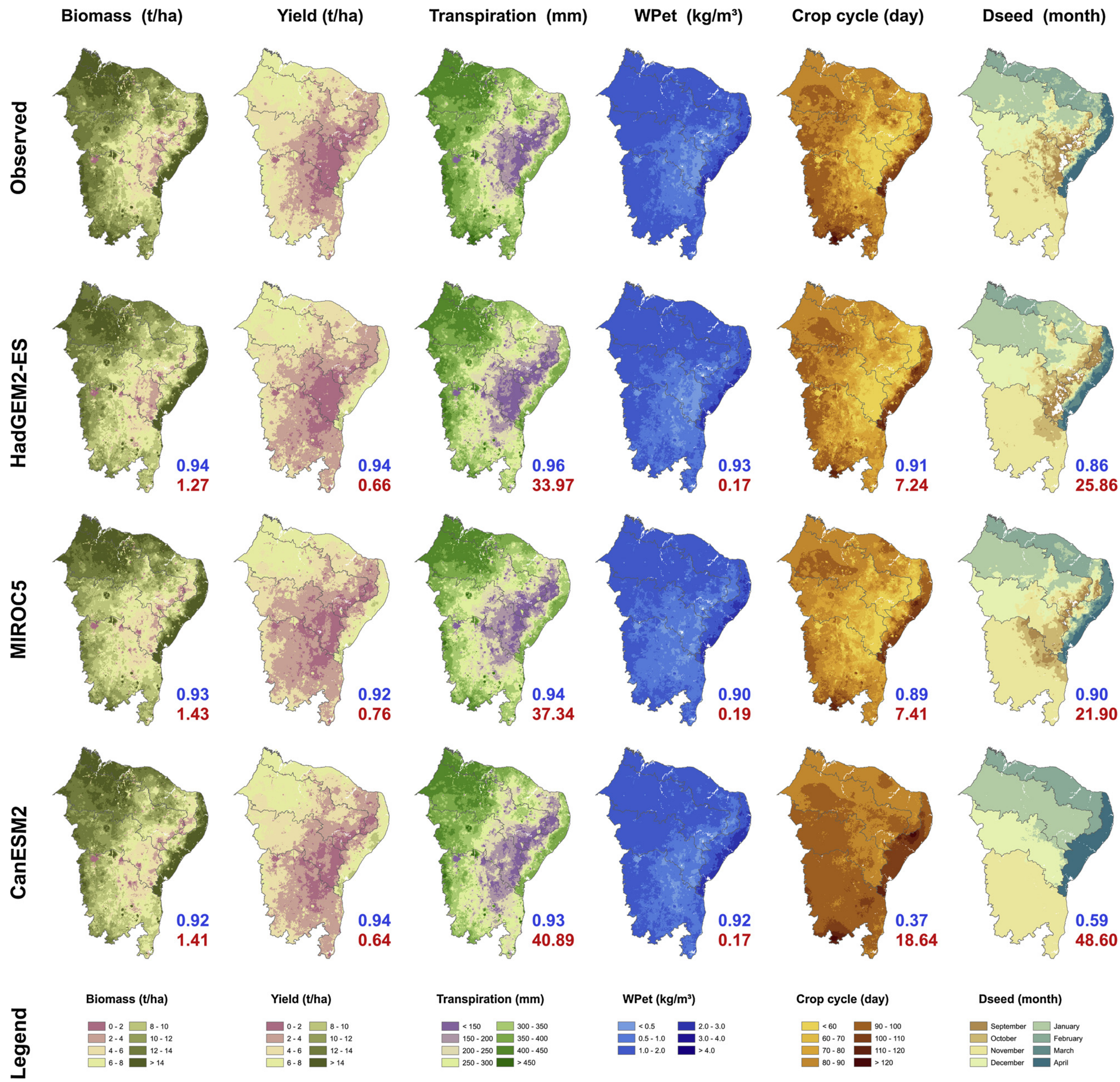

Fig. 2. Comparisons of crop simulations for the baseline period (1980–2005) using different sources of data as the input for the AquaCrop model for Biomass (t ha^{-1}), Yield (t ha^{-1}), Transpiration (mm), Water Productivity - WPet (kg m^{-3}), Crop cycle (day) and Planting Date - Dseed (month). The top row corresponds to simulations resulting from interpolated meteorological data; the second, third and fourth rows are the simulations based on the Eta-Miroc5, Eta-Hadgem2-Es and Eta-CanESM2, respectively. The pixel-to-pixel correlation index between observations and climate model simulations is highlighted in blue, while the root square error is indicated in red (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

reduction of yield. In addition, the decrease of precipitation can negatively affect the transpiration and biomass accumulation, further reducing crop yield.

Based on the mutual interactions of those effects and considering the need to adapt to irreversible climate change effects, the identification of the most effective combination of strategies and technologies for each regional context remains the main challenge of the agriculture sector (Burney et al., 2014). Because the increase in temperature and decrease in water availability are generally the most important causes of yield loss due to climate change, adaptation strategies tested in this study were based on the length of the crop cycle and on water demand. According to Tao et al. (2014) and Zhao et al. (2015), cultivars with a longer growing period can increase the use of potential thermal time as well as improve grain yield.

Therefore, we compared the productivity of existent varieties and fixed the length of the crop cycle to 120 days, which can be achieved using the crop parameters calibrated for CAD against the productivity using crop parameters calibrated for the GDD, which reflects the effects of warmer climate on the length of the crop cycle.

It is important to mention that Aquacrop uses thermal time (GDD) as the default option. When the alternative calendar time is used (CAD), Aquacrop internally estimates GDD, taking into account the upper temperature threshold above which crop development no longer increases with increase in air temperature (Steduto et al., 2009). Therefore, the use of the fixed crop calendar – CAD in warmer conditions implies that the length of the crop cycle will not change for future climate. Since AquaCrop calculations are performed in GDD, fixing the length cycle of the simulations for a warmer climate will implicitly increase the thermal time (GDD) to a magnitude sufficient to fit within the fixed crop cycle, mimicking the behavior of a variety with higher

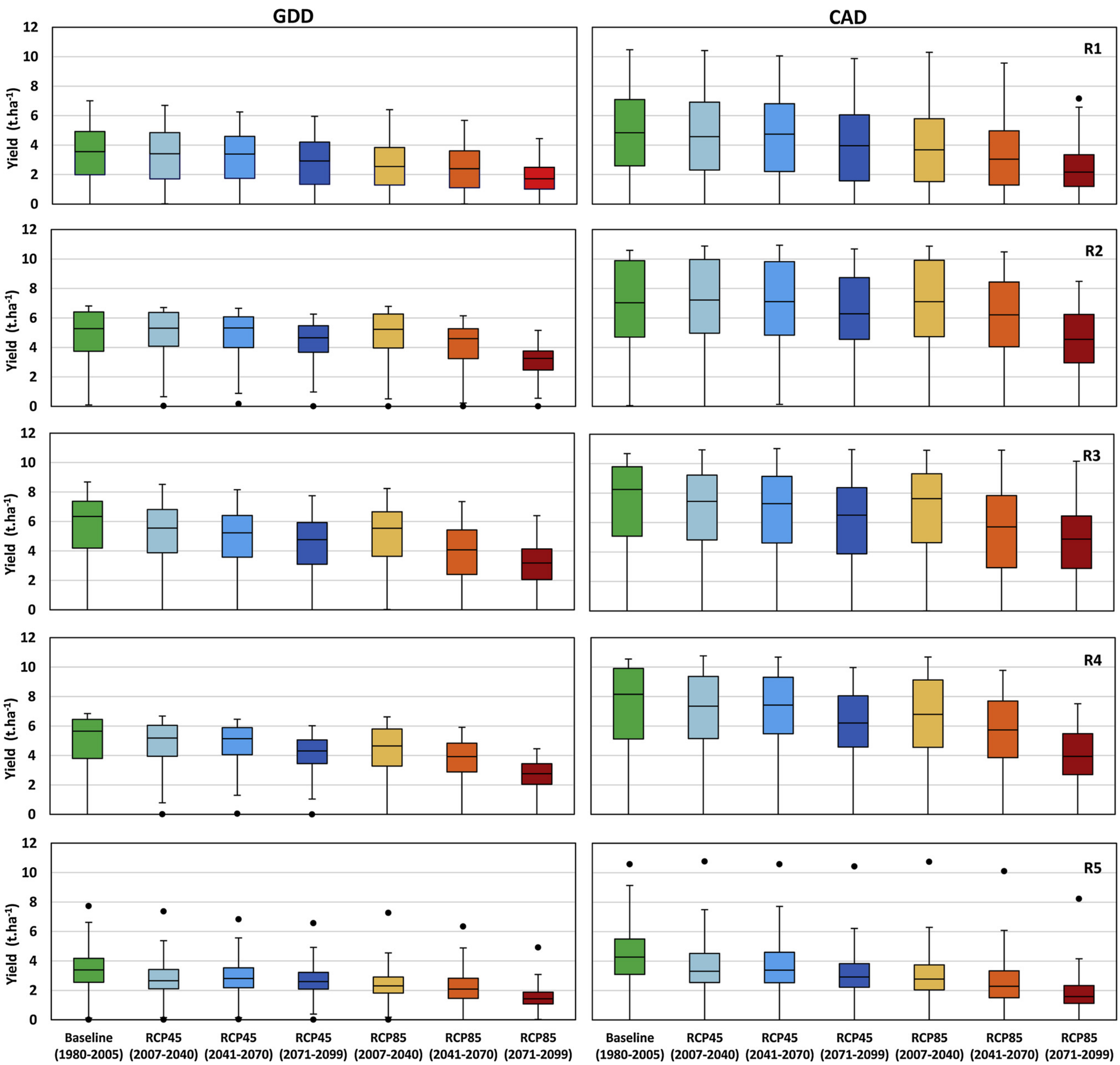

Fig. 3. Box and whisker plots of the projected attainable rainfed maize yield using the growing degree day (left column) and the fixed calendar day (right column), for different subregions (R1-R5) of the study area defined by the four wettest months.

GDD. In addition, all stress coefficients related to temperature and water availability are recalculated to reflect a higher GDD.

In other words, because the growing period of the GDD simulations becomes shorter due to rising temperature, the adaptation option using the CAD parameters implicitly assumes that the length of the growing period remains the same as in 2015, which is equivalent to use varieties with a higher temperature sum that suppress the shortening of the growing period due to warming. A similar approach was used by van Oort and Zwart (2017) to assess the impacts of climate change on rice production in Africa.

It might be argued that the same effect could be achieved simply by increasing the thermal time of GDD simulations. However, genetic variation among cultivars includes not only the variation in timing and duration of the various stages, but also in the initial canopy size per seedling, canopy growth and decline coefficients, rate of root deepening and the response factors to environmental conditions. Although there are limitations in the use of the fixed crop calendar – CAD for future climate, this assumption is further justified by the fact that crop yield data for cultivars with longer crop cycle are not available in the region.

The second adaptation measure tested was irrigation management. Obermaier et al. (2014) showed that irrigation projects implemented in the semiarid NEB contributed to growth in agricultural productivity and, in general, led to income increases: without irrigation, crop losses were in the range of 70%–90% in critical years, while crops with irrigation systems showed losses in the range of 10%–30%. Consequently, we carried out simulations using the net calculation option available in AquaCrop, which quantifies the amount of water needed to avoid water stress effects but disregards the efficiency of the irrigation system, the irrigation method, time-irrigation schedules and limitations of water supply. Thus, the method accounts for the amount of water needed maintain the soil profile at field capacity on a daily basis. Although the net calculation option does not reflect actual field conditions, it is valuable for comparisons of water demand for the baseline and future periods. Therefore, all simulations were repeated to allow for the use of irrigation and comparisons made in terms of productivity for fixed calendar days and growing degree days, as well as in terms of water

requirements. Based on the irrigated areas in 2015 and 2030 (ANA, 2017) and the planted area of maize in 2015 (IBGE, 2016), we estimated the maize crop water demand and production for both historical and future climate change scenarios at the municipal and subregional levels. Irrigated areas for 2015 were used in the historical scenarios, while future scenarios (regardless of the time-slice) used the potential irrigated area estimated for 2030. Unless the IBGE agriculture census provided planted area specific for each crop, the Brazilian Atlas of Irrigation (ANA, 2017) did not specify information on the irrigated area of each crop type. Therefore, we assumed a fraction of the irrigated land was used for maize production based on the information of existent irrigated areas. Values of planted and irrigated areas were multiplied by the maize yield for irrigated and rainfed conditions, and values were accumulated for the 5 climate regions of the study area.

3. Results and discussion

3.1. Maize yield estimations for the baseline period using observations and climate models

Fig. 2 shows the spatial distribution of the average values of biomass, yield, water productivity, transpiration, planting date, and crop cycle length over the baseline period, which was simulated by AquaCrop using, as the input, interpolated observations and bias-corrected Eta downscaled scenarios from the Miroc-5, Hadgem2-ES and CanESM2 global models.

Visual analysis and the statistics clearly revealed close agreement between simulations run with observation and climate models for the baseline period. Almost all variables presented a correlation index above 0.90 (except for the cycle length in the case of the CanESM2 model), which indicates excellent performance from all three models. The root-mean-square error between the simulated and observed variables presented a low value, usually below 16% of the mean values (except the cycle length projected by the CanESM2 model). In spite of the uncertainties of the climate model projections, the good performance of the AquaCrop model using bias-corrected data from model simulations for the baseline periods gives more confidence in the simulations of future scenarios. Calibrated AquaCrop parameters and other statistical evaluations are presented in Table A1 in the Supplementary material.

3.2. Impact of the climate change scenarios on the maize yield

Fig. 3 shows the box and whisker plots of each subregion for rainfed maize yield for different time-slices and climate emissions, using the crop parameters for GDD and CAD. In terms of yield, it is clear that the simulations using the CAD crop parameters were higher than those for GDD. However, the CAD simulations had much larger dispersions compared to the GDD simulations for most of the subregions, which was related to the fact that the subregions were delineated based on the 4 wettest months and, consequently, include areas of high rainfall to the west and east of the study region, as well as areas of the semiarid interior. Because of this, the CAD simulations showed higher productivity than GDD simulations within the rainy areas and lower productivity within the semiarid areas. In other words, although the median productivity of the CAD simulations was higher, the chances for crop failure were also higher, which explains why the cultivars currently used in the semiarid region favor a short crop cycle.

Regarding the future scenarios, there was a clear decrease in yield, which was more drastic in the most distant future and for the highest emissions scenarios for both the GDD and CAD simulations. In subregion 5, for instance, for the 2071–2099 time-slice of the pessimistic RCP8.5, the median dropped by 58% for the GDD and 63% for the CAD simulations. However, for the RCP4.5 scenario, the yield loss was less significant, even though the drop in the median reached -24 and -32% for the GDD and CAD simulations, respectively, in the most distant future in subregion R5. It is interesting to note that the reduction in the yield median tended to be moderate until 2070 for RCP4.5 and until 2040 for RCP8.5.

Comparisons between the CAD and GDD simulations in terms of their sensitivity to climate change indicated that the median relative yield decrease was more pronounced in the case of GDD for subregion 3, while in subregion 5, the results were the opposite; that is, the CAD simulations were more affected by climate change in this subregion. In the case of the other subregions, the results indicated no consistent signal, except in subregion 2, where the performance of CAD was marginally better.

Despite the larger dispersion, the CAD simulations presented a higher yield median compared to that of the GDD simulations. In agreement with the findings of Huang et al. (2018), maize cultivars with a longer growing period were suitable to use as a measurement of adaptation to climate change.

In general, subregion 5 was more affected in terms of the decrease in the maize median yield relative to the baseline, followed by subregion 3, while subregion 2 seemed to be less affected in terms of yield losses.

While there was agreement between all the simulations that the temperature increased in all subregions, the projected changes in precipitation differed among the models in certain subregions, both in terms of the magnitude and in the signal of changes. Subregion 5 has been most affected by the reduction of precipitation since the beginning of the century (see Figure A3 in Supplementary Material), while the most pessimistic scenarios also indicated a sharp reduction of precipitation for subregion 3. With regard to subregions 1 and 4, the climate models diverged in terms of precipitation changes before 2070, but they agreed with the sharp reduction by the end of the century. On the other hand, subregion 2 was expected to have increases in precipitation until 2070. The increase in precipitation was more noticeable under RCP4.5, which caused a slight increase in the maize yield median.

Srivastava et al. (2018) reported an increase of maize productivity in Ghana due to the combination of higher CO_2 concentrations with moderate-to-no changes in the amount of precipitation and incoming radiation during the growing cycle. As concluded by Srivastava et al. (2018), the impacts of climate change on maize yield depend on how changes in temperature and rainfall amounts combine to bring about shifts in the onset and the length of future growing seasons. Because of this, the decrease in rainfall in future scenarios gradually reduces yields by the end of the century in all scenarios, as shown in Fig. 3. A more comprehensive study in Africa by Dale et al (2017) showed contrasting results, which were mostly related to changes in precipitation.

Da Silva et al (2012) showed an increased in climate risk during November and December for NEB. Since that period coincides with the planting date of Sub-region 5, this explain why our results indicate larger productivity drop in that sub-region.

In a background assessment, we verified that the crop cycle length was impacted by up to 14 days shortening, comparing CAD to GDD simulation. Reduction of crop cycle length was also found by Ojeda-Bustamante et al. (2011) in Mexico and Prasad et al. (2018) in Northeast of United States.

To analyze whether the use of irrigation could minimize the loss of productivity due to climate change, Fig. 4 shows the same box and whistler plots as in Fig. 3, except that in these simulations, irrigation was included.

As expected, there was an increase in yield for both the GDD and CAD simulations, although the increase was much more significant for the CAD simulations and much less spread out in each subregion related to the fact that irrigation suppresses the risk of loss related to dry spells. Subregion 3 showed the highest dispersion compared to the other subregions, which was related to higher temperature. In general, the CAD simulations also showed larger dispersion than the GDD simulations, which is likely be related to the length of the growing season

In terms of the median, it is interesting to note that for the current

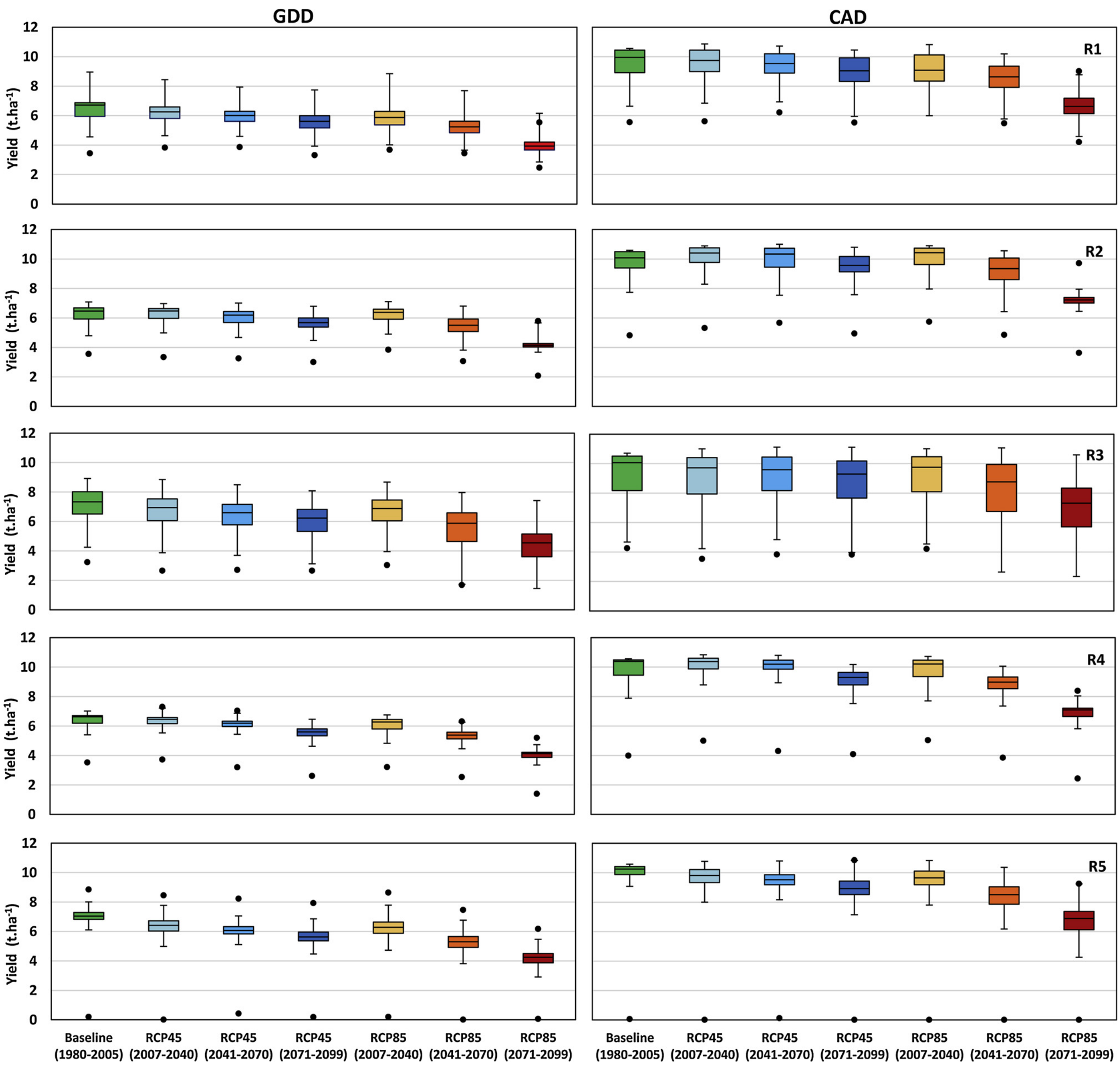

Fig. 4. Box and whisker plots of projected attainable irrigated maize yield using the growing degree day (left column) and the fixed calendar day (right column), for different subregions (R1-R5) of the study area defined by the four wettest months.

climate, the use of irrigation can significantly increase the productivity of maize; in subregion 5, for the baseline scenario 1980–2005, the attainable yield increased from 3.3 to 7.0 t ha^{-1} in the GDD scenario, while it soared from 4.3 to 10.0 t ha^{-1} for the CAD scenario.

Regarding future scenarios, it is clear that the reduction in yield was more significant for the GDD compared to the CAD scenarios in all subregions. For both the GDD and CAD simulations, the reduction in yield for the most unfavorable scenarios was less severe when compared to non-irrigated simulations: the time-slice 2071–2099 for the RCP8.5 scenario in subregion 5 resulted in crop losses in relation to the baseline of 40% and 33% for the GDD and CAD, respectively. These results suggest that, for the worst climate change scenario of subregion 5, yield loss can be reduced by 18% and 30% using irrigation for the GDD and CAD, respectively. In terms of the median, it is interesting to note that the drop in productivity would be moderate for all the RCP4.5 time-slices and for RCP8.5 until 2070. The decrease in median yield was -20% (GDD) and -13% (CAD) for the 2071–2099 time-slice for RCP4.5, and -25% (GDD) and -17 (CAD) for the time-slice 2041–2070 for RCP8.5. It is clear that irrigation compensates for most of the loss of productivity, as suggested by previous studies (Meng et al., 2014; Araya et al., 2017). However, even in conditions with no water stress, crop yield will be substantially reduced by the elevated temperatures, as in the case of the RCP8.5 for 2071–2099. Our results are in agreement with those of Burney et al. (2014), who tested different technologies and arrangements at the farm level and showed that interventions that focused on efficient irrigation systems can help reduce (but not eliminate) the dependence on production systems. Previous results from Dale et al. (2017) attributed the drop in maize productivity in Africa to AquaCrop's high sensitivity to precipitation and low sensitivity to temperature relative to other crop models and statistical analyses (Eitzinger et al., 2013). However, their results used default maize calibration parameters, while in this study, the crop parameters were set by site-specific controlled field experiments (Martins et al., 2018), and our scenarios predict an increase in temperature up to 5 °C in the worst case (see Figure A3 in Supplementary Material).

In addition to the impact of irrigation in productivity, Fig. 5 shows

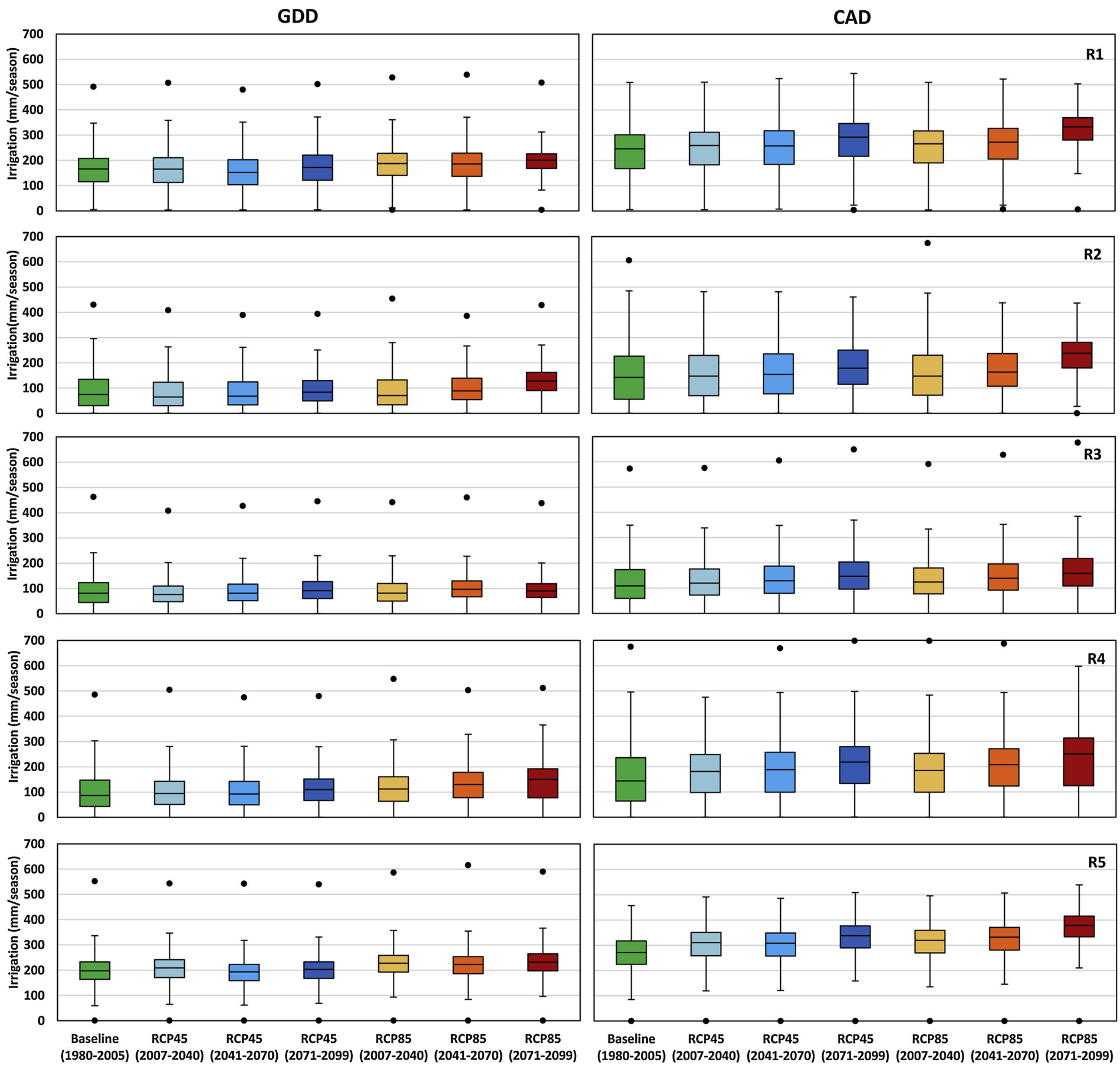

Fig. 5. Box and whisker plots of projected irrigation demand using the growing degree day (left column) and the fixed calendar day (right column), for different subregions (R1-R5) of the study area defined by the four wettest months.

the net irrigation demand for the different subregions and climate change scenarios. As expected, and because the CAD scenario had a longer crop cycle compared to GDD, it had higher irrigation requirements and much dispersion among regions. For the baseline scenario and in subregion 5, the median irrigation demand was 197 mm for the GDD scenario compared to 272 mm for CAD. As mentioned before, the extra water requirement in the case of the CAD scenario (75 mm) implies an increase of yield of 3 t ha^{-1} according to the simulations.

The effect of increased temperature is evident in all future scenarios and directly impacts the crop water requirement, and consequently, irrigation requirement: for instance, in subregion 5, the median of irrigation requirements increased from 271 mm $season^{-1}$ in the baseline scenario to 378 mm $season^{-1}$ for RCP8.5 2071–2099.

It is important to emphasize that we estimated the irrigation requirements based on net irrigation, which does not account for the efficiency of water applications, nor for the amount that maximizes yield. Considering that deficit irrigation could increase water productivity resulting in a yield similar to full irrigation (Mustafa et al., 2017), future studies should consider several options in terms of the requirements and application time-schedules for maintaining high yield under water-limited conditions.

Fig. 5 indicates the irrigation crop requirements for the whole study region and does not explicitly take into account the irrigated areas and areas that are potentially suitable for expansion of irrigation. Therefore, we used data from the rainfed planted area for 2015, the irrigated areas of 2015 and estimations of the irrigated areas for 2030 to calculate the maize production for each scenario and subregion. As we mentioned before, the Brazilian Irrigation Atlas (ANA, 2017) does not provide a fraction of the irrigated areas used for maize crops. Detailed information on few perimeters indicates that the proportion used by maize varies between 10 to 50% of the area. Therefore, for the purpose of this study, we fixed the irrigated area of maize at 30% for both 2015 and 2030 and assumed it was constant across all irrigated areas.

Fig. 6 shows the attainable total production based on the 2015 planted and irrigation areas for the baseline scenarios and the variation in the total production for the future scenarios considering the

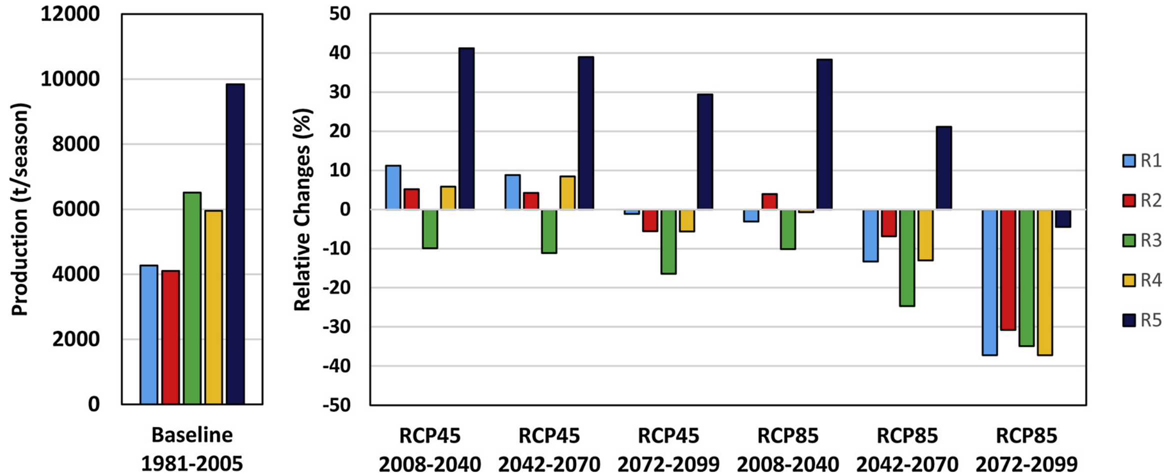

Fig. 6. Total maize production estimated using 2015 rainfed planted and irrigated areas for the baseline scenario for the five subregions of the study area (left panel); changes in each future scenario relative to the baseline (right panel).

estimates for irrigation areas for 2030. For subregion R5, which is the more promising region in terms of the expansion of irrigated areas, the RCP4.5 scenarios resulted in an increase in production, although those gains gradually decreased for the most distant future. In the other subregions, there was a slight variation, plus or minus within 10% of the baseline scenario, for all future scenarios with the exception of subregion R3, where the drop in productivity is approximately -16% after 2072. Regarding the RCP8.5 scenarios, increased production in subregion R5 was verified until 2070, while for the 2072–2099 time-slice, the gains were cancelled out. In the other subregions, production gradually decreased and reached values between -30 and -50% in the most distant future. In other words, potential gains in production due to expansion of irrigated areas were achieved in subregion R5, while the outputs were neutral in other sub regions. In the case of the worst emission scenarios, such as in RCP8.5, gains in production due to expansion of irrigated areas were not enough to compensate for the negative effects of climate change.

Since the use of irrigation at a large scale has strong implications in terms of water availability, Fig. 7 shows the water demand of each of the scenarios, as shown in Fig. 6. Water consumption in subregion 5 was much higher than in the other subregions related to the fact that it has the largest irrigated areas. It is also in subregion 5 where the highest impact of water demand occurred for future scenarios, with an increase that exceeded 140% compared to the baseline for the most pessimistic scenario. A significant increase in demand was also observed in subregion 1, closely followed by subregion 4. All three regions are mostly located in the semiarid area (Fig. 1) where the most significant expansion of irrigated areas are planned. For the worst-case scenario, even subregion R2 showed significant increases in water demand (˜70%). Although the scenario indicated that it would be possible to sustain or even increase levels of production in subregion R5 (Fig. 6), those increases were at the expense of a significant increase in water demand.

Because the Brazilian Atlas of Irrigation (ANA, 2017) takes into account water availability at a sub-basin level but does not consider the effects of climate change in crop water requirements and in river discharges, it is necessary to reassess whether the estimated area for irrigation expansion for 2030 does not have serious implication in other water uses and in ecosystem health. In this case, the results of Fig. 5 will need to be adjusted. This is particularly relevant considering that the Brazilian Adaptation Plan to Climate Change (Brazil, 2016a) warned that the impacts in northeast Brazil are related to the decline in river discharges, which are the main source of water for irrigation.

Burney et al. (2014) drew our attention to the fact that is necessary to have a clear discussion about what kinds of technologies should be purchased with government funds to decrease the impact of drought and build resiliency, by applying the right measures, through time, especially during good rainy years, when the farmer has time and resources to organize his/her farm to face longer droughts.

We recognize that our study is affected by several sources of

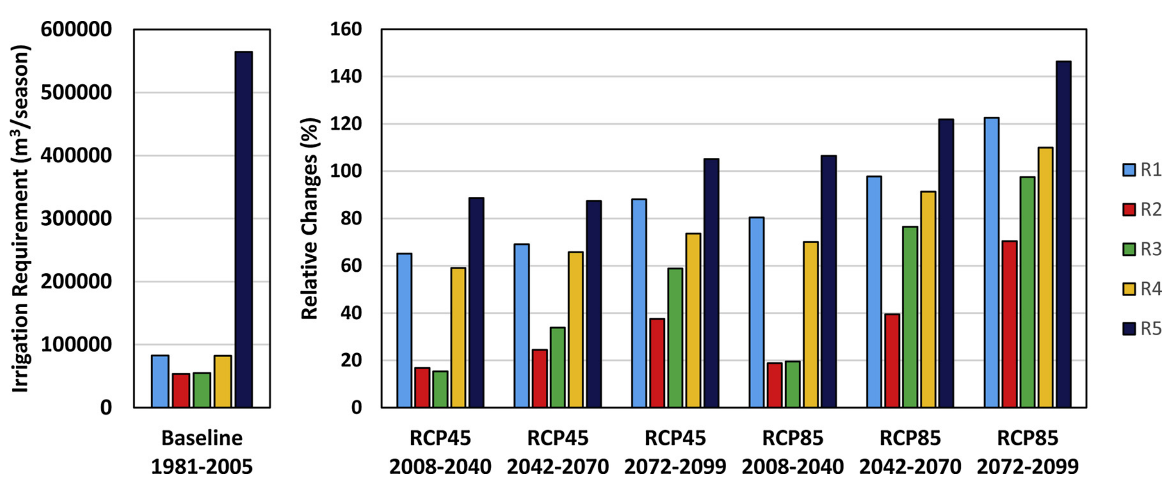

Fig. 7. Irrigation requirements estimated using 2015 rainfed planted and irrigated areas for the baseline scenario for the five subregions of the study area (left panel); changes of each future scenario relative to the baseline (right panel).

uncertainties, especially the projected climate change scenarios and due to the choice of the crop productivity model. However, considering that precipitation contributes to most of the uncertainties in model projections (Dale et al., 2017), it can be assumed that most of the limitations of this study are related to climate change models rather than to the crop productivity model used.

In addition to the models´ limitations, we also ignored the influence of pests, weeds and mycotoxins that can become relevant in a warming climate (Vaughan et al., 2014). We did not account for the effect of soil fertility, since all simulations assumed optimum nutrients levels. Under scenarios with increased productivity, it is likely to assume that more nutrients will be demanded for soil and that climate change impacts will vary depending on soil fertility.

4. Conclusions

We concluded that maize cultivars with longer growth periods and higher thermal requirements could partially mitigate the negative effects of a warming climate on crop production and food security in the study area. Our results indicated that there will be a drop in productivity, mainly at the end of the century, and that no single adaptation can overcome the detrimental effects of the complex interactions imposed by the changes in precipitation, temperature and atmospheric CO_2 concentration.

In general, a drop in productivity is significant for rainfed agriculture. Losses are kept at less than 20% in the case of irrigated cultivars with longer crop cycles for all scenarios, except for the most pessimistic RCP8.5 for the most distant future. In terms of the total production output, which considered the expansion of irrigated areas until 2030, several scenarios indicate that it is possible to increase production, except for the most pessimistic scenario. However, to sustain the current level of productivity, a significant amount of water, up to 140% compared to the baseline in the worst-case scenario, is required.

Our results suggest that it is necessary to develop maize cultivars that use a longer crop cycle and that can adapt and become tolerant to high temperatures. In addition, irrigation becomes essential to sustaining productivity in adverse climate change scenarios.

It is important to mention that climate model projections are meant to produce plausible future scenarios to facilitate the exploration of crop management strategies. Therefore, they cannot be treated as a deterministic prediction of the future climate. In this context, considering the competitive uses of water in the northeast Brazil, such as human and animal consumption and hydropower, it is crucial to examine future demands for different uses in the region, considering that irrigation is likely to become essential to sustain maize productivity levels.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agwat.2019.02.011.

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